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Temporal Impact on Cognitive Distraction Detection for Car Drivers using EEG

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ABSTRACT

Electroencephalography (EEG) has the potential to measure a person's cognitive state, however, we still only have limited knowledge about how well-suited EEG is for recognising cognitive distraction while driving. In this paper, we present DeCiDED, a system that uses EEG in combination with machine learning to detect cognitive distraction in car drivers. Through DeCiDED, we investigate the temporal impact, of the time between the collection of training and evaluation data, and the detection accuracy for cognitive distraction. Our results indicate, that DeCiDED can recognise cognitive distraction with high accuracy when training and evaluation data are originating from the same driving session. Further, we identify a temporal impact, resulting in reduced classification accuracy, of an increased time-span between different drives on the detection accuracy. Finally, we discuss our findings on cognitive attention recognition using EEG how to complement it to categorise different types of distractions.

CCS CONCEPTS

• **Human-centered computing → Laboratory experiments**; **User studies**.

KEYWORDS

Temporal Impact on Cognitive Distraction Detection, Electroencephalography, EEG, Cognitive State Detection, Cognitive Distraction, Distraction Detection for Drivers

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1 INTRODUCTION

Distraction while driving was the cause of approximately 25% of all road accidents in the United States in 2016 [15], and the number of fatalities due to road accidents for that period amounted to 1.4 million people. For the age group 5 - 29, traffic accidents were the number one cause of death, according to the World Health Organisation [14]. Driver distraction can be divided into three main categories: visual, physical and cognitive distraction, and while visual and physical distraction has been studied extensively in HCI research, we lack studies and ways of identifying cognitive distraction, also sometimes referred to as mind-off-the-road. Cognitive distraction is a mental state in which a drivers mind is not focused on the task at hand namely driving the car [2]. While cognitively distracted, the driver's hands can still be on the steering wheel and his/her gaze directed on the road – still, mentally his/her thoughts are focused on something else. While initial studies have started to consider how EEG can be used for cognitive distraction detection, we have limited understanding of how time and temporal aspects of collecting and measuring has on accuracy (e.g., [3, 24]).

In this paper, we investigate how cognitive distraction can be detected while driving using electroencephalography (EEG) and more specifically, we investigate the temporal impact of the data collection time using EEG for cognitive distraction detection. To do this, we design and develop a system for the detection of cognitive distraction using EEG for drivers called DeCiDED. When talking about the *temporal impact*, we refer to the impact of the time interval between the collection of training and evaluation data on the distraction detection accuracy. To the best of our knowledge, no study has been performed which investigates the temporal impact on the detection performance for cognitive distraction between the collection of training and evaluation data has on the distraction detection accuracy using EEG for cognitive distraction detection for car drivers. For a distraction detection system to be relevant for future drives, the performance on future drives, measured using unseen evaluation data, still has to be accurate enough to be able to detect cognitive distraction. All results presented in this paper are on a subject dependent basis, meaning that the training and evaluation data come from the same subject, this has the advantage of being able to define parameters specifically for the individual participant, with the downside of having to parameter tune for each individual.

2 RELATED WORK

Although different types of cognitive distraction have been investigated in different contexts with different methods there is little focus on the use of EEG. In this section, we firstly outline literature on detecting cognitive distraction in general and secondly detecting cognitive distraction with EEG.

2.1 Detecting Cognitive Distraction

Current HCI research has investigated how to detect cognitive states, such as driver fatigue [21], cognitive load [1], or cognitive distraction [6, 22, 25]. Examples for approaches to cognitive state detection include vision, temperature, as well as the state of the car [6, 9, 22, 23, 25]. In addition to the detection of cognitive states, such as fatigue or distraction, the related topic of how to intervene to this has also received increased interest [11, 16, 22, 23].

Salvucci [16] uses computational cognitive models to investigate and predict what effect the performance of a secondary task has on a drivers interaction with surrounding vehicles. Such a study can be used in the development of evaluation tools for user interfaces in complex domains. Trbovich and Harbluk [23] investigate how the visual behaviour of a driver changes while eliciting cognitive distraction by letting the driver interact with a speech-based hands-free cell phone system. They find that such distraction sources might contribute to intersection crashes. This contributes to the importance of guidelines for systems for cognitive distraction detection and alleviation while driving. Tchankue et al. [22] create an adaptive prototype in-car communication system to diminish cognitive distraction while driving. They make use of driving speed and steering wheel angle to detect the current distraction level of a driver. This is used to decide when a user should be allowed to receive calls and send text messages. The results show that such a system provides usability and safety benefits while driving and reduces cognitive distraction. Wesley et al. [25] identify cognitive distraction by measuring the thermal signature of the face of the driver. They find the changes in thermal signature while cognitive distracted to be measurable. Fridman et al. [6] develop two vision-based methods to identify cognitive load while driving. They use a video recording of the driver to identify the current pupil position. Based on their findings, they conclude that it is possible to identify cognitive load while driving through analysis of drivers' vision.

2.2 Detecting Cognitive Distraction with EEG

Electroencephalography (EEG) is a method of using electrodes to detect the brains electrical activity. In contrast to other methods that use electrodes, such as intracranial electroencephalography (iEEG), EEG is non-invasive, as the metal electrodes are placed on the scalp and not directly on the brain itself.

Correlations have been found between EEG signals and the distinction of cognitive distraction from focus, which enables the development of an automatic attention recognition system. Wang et al. [24] create a support vector machine-based system using EEG signals, to distinguish cognitive distraction from focus of drivers in a dual-task experiment of lane-keeping and solving math problems. They achieve 84.5% and 86.2% classification accuracy for math solving and driving respectively. Almahasneh et al. [3] examine how EEG signals change when a driver is presented with different cognitive secondary tasks. They found that different secondary tasks had different effects on EEG responses and different locations on the cortex. However, the most affected area during distraction was the right and left frontal cortex region. This suggests that these areas should be investigated when working with cognitive distraction while driving.

3 DeCiDED

We designed and implemented a system for the detection of cognitive distraction using electroencephalography (EEG) for car drivers. We call this system DeCiDED. DeCiDED makes use of a 3d-printed EEG helmet to collect data for the detection of cognitive distraction while driving. We printed the helmet in two different sizes using a 3d printer to allow subjects with different head sizes to participate in our study (hardware cost: ~400$). Furthermore, we developed a low-fidelity driving simulator using Unity3D[1] to maximise customizability of the driving environment.

The setup can be seen in Figure 1A and the conceptual illustration of the distraction detection component of DeCiDED can be seen in Figure 2.

We used the OpenBCI Ultracortex Mark IV 3D printed helmet (Mark IV), as seen in Figure 1B, and the OpenBCI Ganglion biological sensing device (Ganglion) [13]. Mark IV can target 35 electrode locations of the 10-20 sensor placement system. Ganglion can target 4 locations at a time, using Sensor Units as shown in Figure 1C, has a sampling rate of up to 200Hz and uses ear clips for reference signals. We made use of the sensor locations F3, F4, C3 and C4. Almahasneh et al. [3] identified an increase in brain activity in the frontal lobe during distraction [3]. We, therefore, chose the location F3 and F4 (frontal), which are part of the right and left frontal lobe respectively, to be part of our sensor locations. C3 and C4 (central) were chosen based on Ibáñez and Iglesias [8], who identified their importance when it comes to cognitive distraction. The driving simulator made use of the Thrustmaster T80 steering wheel and pedals, as well as a 32" full HD monitor for the centre view, and two 23" full HD monitors for the side mirrors.

The component for collecting and processing data, as well as detecting cognitive distraction makes use of 10 Random Forrest Classifiers (RFC). The system identifies features (Higuchi Fractal Dimension, Petrosian Fractal Dimension, Band Power Ratio and Discrete Wavelet Transform), to recognise patterns to distinguish cognitive distraction from focus within the EEG data. The input to the system is the raw EEG data which is transmitted via Bluetooth to a nearby laptop. In the 1 Segmentation step, the data is segmented into smaller time windows. Since DeCiDED is used in a safety-critical environment, fast update times are crucial. For this reason, we have chosen a time window length of 2 seconds, with no overlap [2], which enables DeCiDED to detect if the driver is cognitively distracted or focused for each 2 second time window. Furthermore, 1 divides the collected data into training and evaluation data, where the first part is used to train the system by identifying patterns, and the second part is used to evaluate its performance on new, unseen data. The ratio for the data division between training and evaluation data depends on the experiment

[1] https://unity.com

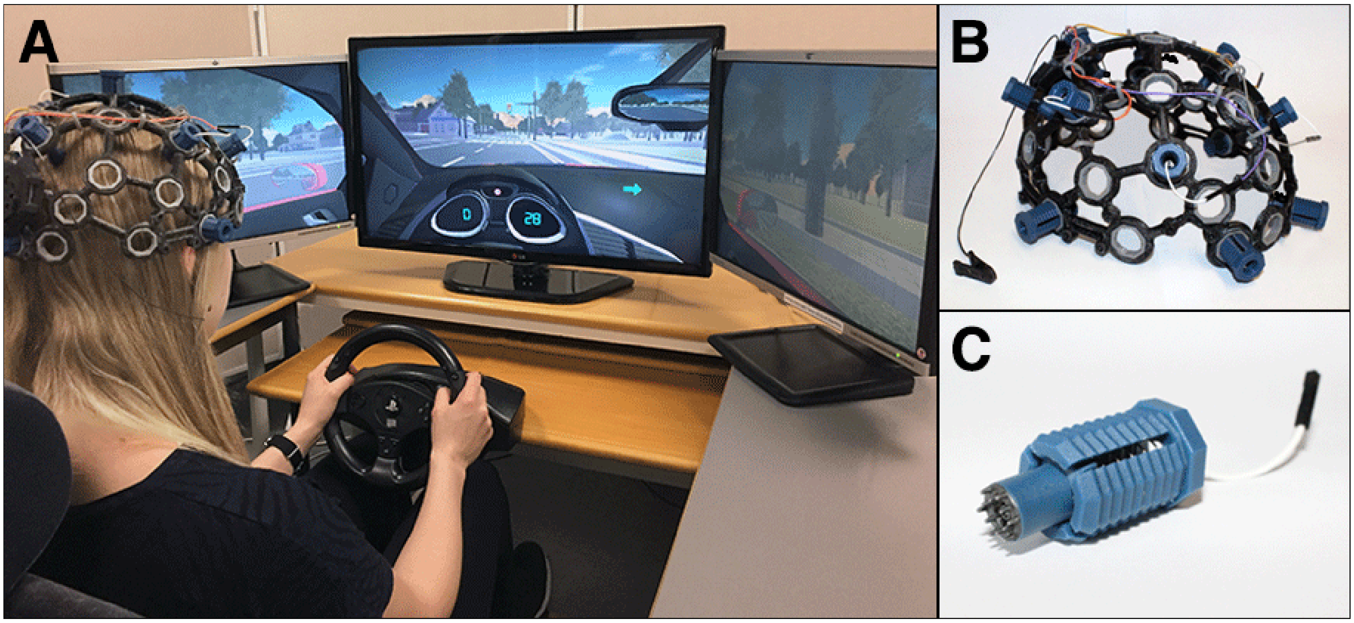

Figure 1: A Three monitor driving simulator with the Mark IV in use. B Mark IV close up. C Sensor Unit close up.

setup which will be described in Section 5, referred to as (Ⓐ Same Day(s) & Ⓑ Between Days).

The ② Cleaning & Extraction step takes the, into 2 seconds segmented, data as input. To achieve a better signal-to-noise ratio, we removed noise from the data by applying filters to it. Since all classification was performed on a subject dependent basis, different filter parameters were set for each individual. The filters used varied between notch and high-pass filters, depending on the subject. A high-pass filter removes signals under a given threshold, whereas a notch filter removes signals within a given interval. Noise can, for instance, be present in the form of electromagnetic interference which can be caused by e.g. power lines. In addition to applying filters to the data, to remove noise retrospectively, we made sure that the same electronic devices were present during each driving session. By reducing the number of devices present, we made efforts to reduce the potential for electromagnetic interference during the data collection. Furthermore, step ② extracts features from the data. The 5 individually best features are, in the ③ Selection step, greedily selected and combined in pairs/triads (k = 2 or k = 3). The best feature combination dependent on the individual test subject. For each combination, an RFC is trained which results in a total of 10 RFCs, see equation 1. n is the number of available features, in this case, 5, and k the amount selected features for each combination, here 2 or 3. Each of the 10 resulting RFC's classifies each 2 second time window of the evaluation data set as either distraction or focus. A majority vote then decides the final classification. The value for k as well as the best attributes and filter vary between subjects since the system is subject dependent.

$$C(n,k) = \frac{n!}{k! \times (n-k)!} \tag{1}$$

4 USER STUDY

Our study aimed to explore the temporal impact on the classification accuracy of cognitive distraction using EEG. To identify the temporal aspect, we utilised two different approaches. Firstly, we studied cognitive distraction detection accuracy on data where both the training and evaluating data set where collected on the same day. Since these where both collected during the same session, the time between this data collection was minimised. Secondly, we studied cognitive distraction detection accuracy using data sets collected on two different days. For this case, the training data was collected during the first driving session, and the evaluation data was collected during a separate session performed seven days later. By using this approach, we can compare classification performance for data originating from the same day as well as with a seven-day temporal delay, thereby identifying the temporal impact on the classification accuracy.

The user study consisted of two essential parts, using the same procedure. Ⓐ The identification of the systems ability, and replicability, to detect cognitive distraction, without the increased temporal impact of increasing time between the collection of training and evaluation data. For this purpose we divided the data collected for both days into 70% training and 30% evaluation data, we call this data division "Same Day(s)". This was done for both days independent of each other. Ⓑ The identification of the temporal impact on accuracy when using EEG for cognitive distraction detection. This was investigated by increasing the time between training and evaluation data collection. Here the entirety of the data collected on day 1 was used for training and the data from day 2, collected 7 days later, for evaluation. We call this data division "Between Days". It is important to mention, that this study makes use of two separate conditions to distinguish between focus and distraction given the used elicitation method.

Figure 2: Conceptual illustration of DeCiDED. From Raw EEG data to Classification.

4.1 Participants

Eight people participated in our user study (5 males; 3 females; age between 21 and 55, mean = 31, SD = 13.9). The yearly driving distances varied between 2500 to 60000 kilometres per year (mean = 21750, SD = 18704) according to own estimates. All test participants were recruited using word-of-mouth, online postings, as well as flyers. None of the participants was paid or informed of the exact purpose of the experiment. Since the audio-book condition required listening to a danish audiobook, we only recruited test participants who were fluent in the Danish language, thereby reducing the potential impact of missing language skills.

4.2 Elicitation Methods

Within the field of cognitive distraction elicitation, a multitude of methods has been proposed. Among others are listening to the radio, solving mathematical equations, listening to audiobooks and the usage of hand-held devices [3, 19, 20, 24] to mention but a few. When it comes to the elicitation of cognitive focus, a broader consensus exists. Jin et al. [10] propose the use of no secondary task. Lin et al. [12] concluded that the deprivation of sensory stimuli while driving increases the likelihood of the driver to lose focus from the road. After several pilot tests, approaches inspired by [10, 12] for the elicitation of cognitive focus, meaning the use of no secondary task in a stimulating environment. After experimenting with different elicitation methods for cognitive distraction, amongst others radio listening, small-talk during a telephone call, listening to music, as well as small math-problems, we chose to elicit cognitive distraction using the audiobook approach, as described by Sonnleitner et al. [19]. For this, we made use of the same audiobook, "Seven Years in Tibet" as [19]. To remove any language barrier we made use of the Danish version.

4.3 Task

For the elicitation of cognitive focus and cognitive distraction two separate tasks where used. Each task was performed, on each of the two days, for 15 minutes by each test participant. In the cognitive focus condition, test subjects would drive in the environment for 15 minutes. They were instructed to follow traffic regulations, such as speed limits, stop lines, as well as intersections and traffic lights. During this task, a green arrow would show up on the dashboard, as illustrated with a right-pointing arrow in Figure 1A when closing into an intersection. The arrow would indicate the randomly chosen direction (←, ↑, →) the test subject had to drive in the next intersection. Based on [10, 12], we implemented a variety of stimuli,

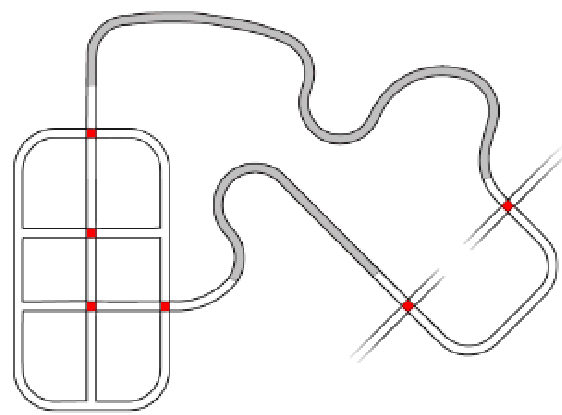

Figure 3: Road network of the driving simulator. White road: 50km/h limit, grey road: 80km/h limit, red: Intersection with traffic lights.

all traffic-related, and no secondary task - thereby increasing the likely hood of focus on the driving. Examples include other AI drivers, traffic lights as well as different speed zones. An illustration of the road network (without houses, trees etc.) can be seen in Figure 3.

For the cognitive distraction task, the driving task was the same. The only difference was the addition of a secondary task, namely the audio-book task, as inspired by Sonnleitner et al. [19]. While driving, again following traffic rules as well as navigational instructions, the test subject would listen to the audio-book "Seven Years in Tibet" (Danish version). Upon detecting the word "and" ("og") they would press a button on the steering wheel to acknowledge this. To remove advantages for right or left-handed people, test participants could press a button on either side of the steering wheel upon detecting the word "and".

4.4 Driving Simulator

To collect EEG data for cognitive distraction and focus, we developed a driving simulator that was used in a lab study.For ethical/safety reasons we could not conduct a field study [4] since the elicitation of distraction behind the steering wheel was part of the user study. We implemented our driving simulator, using Unity3d, since existing driving simulators had limitations in terms of steering wheel support, management of the environment and functionality.

4.5 Procedure

Upon entering the lab, the test participant received the information about the procedure, which was followed by the signing of the informed consent form. Following this, the Mark IV helmet was attached, while ensuring that the impedance for all sensors was below 30kΩ as recommended by the OpenBCI documentation. For these measurements, the official OpenBCI software was used. After the attachment of the EEG helmet, the test participant could familiarise themselves with the simulator, to get used to the steering wheel and pedals. This was done in a specifically designed test course to prevent familiarisation with the test track used in the experiment. For this, the first author was present to answer any potential questions as well as making sure that all different types of stimuli have been encountered in the familiarisation drive.

The driving environment contained both city and rural streets, as well as several other stimuli such as traffic lights, other traffic, stop lines and directional arrows. These design choices were made to 1) mimic real traffic conditions, and 2) provide stimuli for improved cognitive focus elicitation during the driving task [10, 12]. While driving randomly generated turn signals were presented to the driver when approaching an intersection. Both for the cognitive focus and cognitive distraction scenario the same environment was used, with the addition of a secondary task for distraction. In this condition participants listened to the audiobook "Syv år i Tibet" by Henrich Harrer (Seven Years in Tibet), and were instructed to push a button, each time they heard the word "og" (Eng. "and") [19].

The same procedure was repeated approximately 7 days later using the same test participants. This was done to identify the replicability of the results. Furthermore, the second dataset was needed to investigate the temporal impact on classification accuracy as describes for Between Days in Section 5. To remove ordering effects, such as learning effect or fatigue, participants were asked to drive the distraction and the focus condition in a perfectly counterbalanced measure design [17]. This led to four distinct orderings, each driven by two test participants.

5 RESULTS

In this section, we present two results of our study related to using DeCIDED. The experiment yielded two results in terms of classification accuracy, as presented in Table 1. All results presented are on a subject dependent basis, meaning that the numbers presented in Table 1, are the average accuracy for each test subject when trained and evaluated on his/her data.

Our system was able to identify, on average for both days, cognitive distraction with an accuracy of 97.99%, represented with Same Day(s). Same Day(s) is the averaged performance for distraction detection on day 1 and day 2 individually, both with a 70% training and 30% evaluation data division. Each participant had ∼ 7 days between their day 1 driving session in the simulator and day 2. For each of those two days, we achieved classification accuracy ranging from 97% (average for day 1, N = 8) and 99% (average for day 2, N = 8), on an evaluation data set of ∼ 2200 data samples for each day, thereby confirming the replicability of the user study from day 1 to day 2. This identification was important to be able to use this as a baseline for the identification of temporal impact which is the second result. Further, this finding indicates, that indeed data for the differentiation between cognitive focus and cognitive distraction can be acquired using the four sensors (F3, F4, C3, C4) using the specified scenario.

The second row in Table 1 shows us, that when increasing the time between the collection of training and evaluation data, and thereby investigating the temporal impact of the data collection on the accuracy, the accuracy is decreasing. We could identify that DeCiDED was able to identify 76.77% of all cognitive distraction samples correctly, which corresponds to 5594 out of 7287 2-second time windows across all test subjects. Although the results still indicate a tendency towards correct classification, with 76.77% (SD: 10.56), the temporal impact of the 7 days between training and evaluation data is noticeable, illustrated with the 21.22 percentage points drop compared to the individual day baseline. Despite the reduction in accuracy for the Between Days condition, the classification accuracy was for all test subjects still far above the chance level (50%) with a minimum accuracy of 68.89% and a maximum accuracy of 99.56%.

Experiment	Mean accuracy (SD)	Abs. nr.
Ⓐ Same Day(s) (N=8)	97.99% (2.74)	4285 / 4373
Ⓑ Between Days (N=8)	76.77% (10.56)	5594 / 7287

Table 1: Mean accuracy and standard deviation data division Ⓐ Same Day(s) and Ⓑ Between Days.

6 DISCUSSION AND FUTURE WORK

In this paper, we have investigated the temporal impact on distraction detection using EEG. Our results are promising when using the described audiobook task as a distraction elicitation method. In this section, we discuss these results against existing work and how our results can be used in future research on cognitive distraction in cars.

6.1 Detecting Cognitive Distraction using EEG

We show in this study that the audiobook approach can be used to achieve promising results, even though an accuracy decrease can be identified with an increase of time between the collection of training and evaluation data. Wang et al. [24] show that EEG can be used, using a Support Vector Machine, to achieve ~85% classification accuracy between the primary task of lane-keeping, and a secondary task of solving math problems to elicit cognitive distraction. In contrast to this, we made use of a different secondary task using an audiobook listening task inspired by Sonnleitner et al. [19], and achieve an average classification accuracy of ~98% using an RFC. Thereby showing that EEG can achieve promising results for cognitive distraction classification, in the context of driving, with different elicitation methods and classifiers.

Alizadeh and Dehzangi [2] show, that a distinction of 7 different distraction methods is achievable. They achieve 98.99% classification accuracy, which indicates that the difference in the EEG signal, between any of these seven, is significant enough to be distinguished. This might imply, that a distraction elicitation in a different manner, compared to the here applied audiobook approach, might not be recognised by DeCiDED. A future area of research could investigate the robustness of DeCiDED when it comes to its ability to identify alternative cognitive distractions. Furthermore, as most studies of cognitive distraction in cars are carried out in lab settings it would be interesting to investigate how a system like DeCiDED would perform in an in-the-wild study, without artificial elicitation of distraction. Since this would change the study to a less controlled environment, the relevance for multiple distraction detection, as performed by e.g. [2], would become increasingly relevant.

We observed a performance drop of 21.22 percent points when detecting cognitive distraction, for the data division Ⓑ Between Days compared to the results achieved during for individual days during data division Ⓐ Same Day(s). This points at a temporal impact, leading to a decrease in classification accuracy with the increased time between the collection of training and evaluation data. Further research in the field of cognitive distraction detection for drivers using EEG is needed, to investigate efficient countermeasures of the temporal impact, before it can effectively be used. To be applicable, a system for driver distraction detection would need to be able to detect distraction, once trained, on future drives. A potential explanation and topic for future research could be the optimisation of the trained model, using new data, after each drive. Thereby the diversity of mental states which lay the foundation for the model would increase. It is left for future work to investigate this problem further.

6.2 Beyond Classifying Cognitive Distraction

We see EEG as applicable in contemporary research domains that focus on drivers cognitive load to detect when drivers become distracted such as take over requests in semi-autonomous driving (e.g. [5, 26]). However, while we were able to classify cognitive distraction with high accuracy using EEG our data does not provide any conclusions on the reason behind such as if distraction occurs internally like mind-wandering or occurs because of external conditions like being distracted by noise or visuals. We believe that such conclusions are important as well and, although not within the scope of DeCiDED, we argue that moving beyond just classification could be achieved using complementary research methods.

Using DeCiDED as a complementary method for detecting cognitive distraction within a certain accuracy while complementing other means of studying distraction while driving. Doing this we could draw inspiration from related literature on the area cognitive states (e.g.[1, 6, 9, 22, 25]). Such studies typically focus on one type of cognitive states such as eyes off the road, with measurements on e.g. eye tracking [9] or distinction of different cognitive loads depending on task difficulty using thermal imaging [1]. For example, Jensen et al. [9] detects eyes off the road using eye-tracking in driving situations. However, while this method of tracking visual distraction is less obtrusive, they only detect when eyes are off the road and therefore not mind off the road which we know according to [2] is also a contributor to road accidents. Mind off the road could be detected with the use of EEG, but similarly to eyes off the road, it is indecisive. We believe that combining such methods can aid in the identification of when the eyes are on but the mind is off the road. Similarly, thermal imaging [1], has been demonstrated to be quite unobtrusive and accurate in a lab setting. Thermal imaging adds a new type of problem to studies in the wild in the car, such as temperature fluctuations caused by the AC or outdoor temperature. It could be interesting to investigate the combination with EEG to gain detailed insights about cognitive states in field experiments.

6.3 Applicability of the proposed System In-The-Wild

While we in this study demonstrate the viability of EEG for the binary classification during a lab study, either cognitive focused or cognitive distracted, the here proposed setup brings a multitude of different challenges with it. Firstly, the Mark IV helmet, as well as many other alternative systems, are quite intrusive which does not benefit the day to day application possibilities. Secondly, the attachment process of the helmet is no trivial task requiring conductive gel and assistance to achieve a reasonable signal strength. Furthermore, the Mark IV, although not hurtful, can be quite unpleasant to wear for an extended period. Several alternative solutions have been proposed (e.g. [1, 7, 18]). Two alternative approaches using EEG are the LIFE by SmartCap [18] and the Ear-EEG as presented by Goverdovsky et al. [7]. LIFEs approach is the use of a headband, which can be easily equipped without the need for conductive gels, which measures EEG waves consumer-friendly. LIFE is at the moment still limited to the detection of fatigue and not cognitive distraction, although the potential for a variety of areas is given. The Ear-EEG makes use of an earpiece, to unobtrusively give a user-friendly way to measure EEG signals, without the assistance of a professional for the application of the earpiece. Goverdovsky et al. [7] show that the Ear-EEG achieves a similar signal-to-noise ratio than a classical on-scalp EEG. Abdelraham et al. [1] investigate the feasibility of thermal imaging of a persons nose and forehead for detection of different cognitive states when conducting the Stroop test. They show that thermal imaging can be used as an unobtrusive way to distinguish between a person's cognitive state. It would be interesting to identify the viability of this approach in the context of car driving in-the-wild. While the thermal camera approach has the benefit of being unobtrusive, since no attachment to the head is necessary, it also brings with it a multitude of new challenges. The car as a context, compared to the lab [1], has higher fluctuations of the environmental impact that could affect the thermal readings, such as air conditioning or change in weather. Thereby drastically increasing the difficulty of this approach for in-the-wild studies.

7 CONCLUSIONS

During this study, we investigated the possibility to use EEG signals to detect when a car driver is cognitively distracted. To measure EEG data, we made use of the OpenBCI Ultracortex Mark IV helmet. We developed a driving simulator that was used during a user study with 8 different test participants, resulting in a total of 16 driving sessions, 2 driving days for each participant with 7 days in between. The driving environment was designed to elicit cognitive distraction as well as cognitive focus for the two different conditions. Cognitive focus was elicited by providing a variety of stimuli within the driving environment, without the introduction of a secondary task. For the cognitive distraction elicitation, we used an audiobook approach, as described by [19], to divide the driver's cognitive attention between two tasks. Using machine learning principles, such as filtering and feature selection, we developed the system for the Detection of Cognitive Distraction using EEG for Car Drivers (DeCiDED), which used the collected data to detect if 2-second time windows in the evaluation data represent a cognitive distracted or focused state. Based on the data measured, DeCiDED achieved the following two results.

1) The subject dependent distinction between distraction and focus is possible, with high accuracy, if both the training as well as the evaluation data are measured on the same day. These results are repeatable, which was demonstrated by repeating the data collection on a second day, 7 days after the first day, still achieving comparable accuracies. On both days the results were between 97% to 99%, which were achieved overall test subjects. On average over both days, represented with the Same Day(s) data division, DeCiDED achieved the classification accuracy of 97.99% (sd = 2.74), which corresponds to 4285 / 4373 correctly classified 2-second time windows. 2) When investigating the temporal impact on the accuracy, by increasing the time between the collection of training and evaluation data by 7 days, the detection accuracy dropped significantly, indicating a strong temporal impact. A detection accuracy of 76.77% (sd = 10.56) was achieved, which is a decrease of 21.22 percent points. The accuracy corresponds to 5594 / 7287 correctly classified 2-second time windows.

We discuss the accuracy of EEG and the use of different elicitation methods. Further, we discuss that EEG can be used as a complementary research method for detecting cognitive distraction. As such, we argue that EEG can be used along with other methods such as eye-tracking or skin temperature monitoring might cover the full spectrum of distraction (e.g., eyes and mind off the road).

7.1 Limitations

For this study, we made use of an audiobook approach to elicit cognitive distraction. While high classification accuracies were achieved, pointing towards a division of cognitive resources between the two tasks, we have no information on how the developed system would perform given a different elicitation approach. Examples could include math task solving, receiving a phone call or small talk with a passenger. Furthermore, the classification accuracies presented here are only applicable in a lab study within a controlled environment, even while using the audiobook approach for the elicitation of cognitive distraction, we have no indication about how the system would perform in an in the wild study. The investigation of this is left for future research.

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